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Determination of Rate of Degradation of Iron Plates Due To Rust Using Image Processing -A Review

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Abstract: most of industries and bridges around us make use of iron for manufacturing their products. On the other hand corrosion is a natural process that deteriorates the integrity of iron surface. Therefore, rusting of iron takes place. To avoid unwanted accidents in industries and bridges, it is necessary to detect rusting in earlier stage, so that it can be prevented. Digital image processing for the detection of the rusting provides fast, accurate and objectives results. In this research paper, we have done a systematic review of algorithms that help us to detect the rust area from a metal (iron).it has been found that most of researches are bring their images, processing series in usage for this purpose due to its simplicity in implementing and due to fact the images help capturing the visual inspection process easily and due to the ground teeth. The image processing techniques explored by other peoples based on in-depth analysis, we have also proposed a novel technique to overcome the limitation.

Keywords: Rust detection; Visual Inspection; Image processing

I. Introduction

Rust defect assessment is important in order to maintain a good quality of iron based fabrication painting. Rusting caused by corrosion causes wastage of iron materials, reduction in efficiency and costly maintenance [1]. So, Iron fabrications are more realistically to develop long-term cost-effective maintenance programs if they have dependable coating condition data. In order to detect rust defects in advance it is possible for engineers to initiate corrective action, whether to paint immediately or later or either replace the iron part or to add support like fish plates. Detection of onset of rust is relatively easier in machines, but difficult in bridges which may be located in remote locations and as such not accessible regularly for inspection. Otherwise also even if the bridges are located in populated areas certain portion of them may not be clearly visible thereby making detection of rust difficult [2]. So, due to unreachable location of rust formation either we use some moving robotic instrument or any stationary camera which continuously monitoring or after some interval the effective place respectively. In these cases image processing can be of immense help as rust formation and rate of decay can be calculated using the images captured at different intervals by digital camera or by moving robotic. Image processing refers to any form of signal processing in which input is an image, like a photograph or a video frame, the output of image processing may be either an image or characteristics or some parameters relating to the image[2].Image processing is carried out on a digital photograph or a video. Digitization includes sampling of image or video and quantization of sampled values. After converting the image into bit information, processing is performed. This processing technique may include some pre-processing (like Image enhancement, Image reconstruction, and Image compression, Image crop, Image Rotate) and post-processing steps (unsupervised clustering) which can help us to detect the rust better and in least possible time[3]. Each of this

technique has advantages and disadvantages which are discussed in further sections and also there are multiple methods for detection of rust which are discussed in related work.

II. RELATED WORK

Most research has gone into identification of rust area detection using varied methods. One of them was Sindhu et al [1], he demonstrated the detection of rust on highway steel bridges using **Wavelet Domain Detection of Rust** Technique. It was a non-iterative approach based on the concept of wavelet transforms for the calculation of the rust percentage in the image. The method followed the concepts of principal component analysis and classification of rust and non rust part. Since, in this technique colored images are directly processed, therefore, there is no loss of information. They had implemented training and learning algorithm to classify a given image as a rust or non rust. Since it used the fuzzy logic which was very complex process as it required a lot of training images and all the images used had similar dimensions so because of this, some

part of images remains undetected which is the one of the drawback. However Pidaparti *et al* [17] used an image analysis based on wavelet transforms and fractals to study the corrosion morphology of nickel aluminum bronze metal under varying corrosion conditions. Image feature parameters were extracted and analyzed to classify the pits/cracks in the metal samples. The results indicated that classification of pits/cracks is possible with image analysis and may be used for correlating service/failure conditions based on corrosion morphology.

MichikoYamana and Tohru Ohashi [5] have proposed idea about classification of rusted images with the help of **Support Vector Machines.** In this technique, the images that are taken by a digital camera are classified into "reuse" or "retire" on the basis of the color of the rust. The image taken by the digital camera is fed to the attached computer which compares the same with database images and the classifier function classifies the image as "Reuse" or "Retire". However the results of this paper was promising their accuracy was 100 %,but work was limited by its learning process which was very time consuming and also once we had constructed the classification function, it cannot be change again and due to this it gives limited results.

Mariana P. Bento and Geraldo L. B. Ramalho [6] proposed an approach to detect corrosion of metals based upon **Nondestructive Evaluation (NDE) and Self Organizing Mapping (SOM) using Gray Level Co-occurrence Matrix (GLCM**) for the detection of the change in texture of metal surfaces. Further, Self Organizing Mapping (SOM) is used for the classification of the images as rusted or non-rusted areas of metals. In this experiment, 93% of validation data set was correctly classified but it was a complex process which required multistep methodology. Choi and Kim [13] have also used Co-occurrence matrix for texture analysis. To calculate corrosion surface damage color they used the interpretation of Hue Intensity Saturation (HIS) model. For the texture attributes, the method of co-occurrence matrix was used. Five types of corrosion damage were examined by the author. Multidimensional scaling procedure was used to define the classification plane. The study suggested a probabilistic method of decision-making for that. Zaidan *et al* [15] have also used texture analysis technique for the detection of corrosion in metals.

Besides image processing, other methods have also been used for detecting corrosion. Grinzato et al[16] have used transient infra red (IR) thermography for hidden corrosion detection in thick metallic components. Silva *et al* [18] have used laser ultrasonics and wavelet transform signal analysis for hidden corrosion detection in aircraft aluminum structures.

The potentiality of image processing techniques for automatic rust steel detection was investigated and the methodology introduced an iterative multivariate data analysis to examine the effects of rust steel descriptors, that was texture and color distribution on a set of classification algorithms. In this analysis, a selector of classifiers indicated that algorithm provides good classification results (high sensitivity) and acceptable time response for the automation of the system.

In 1981, Itzhak et al employed computer image processing techniques for statistical evaluation of pitting corrosion in a plate of AISI 304L stainless steel exposed to a corrosive water solution containing 10% Iron (III) Chloride. The purpose of this work was to introduce and to evaluate new tools for analyzing the effects of pitting corrosion process [15]. The algorithm was capable of estimating the number and area of pits in the binary image and therefore provided better evaluation of pitting corrosion damages.

A popular image processing algorithm for texture analysis extracts features from the gray level co-occurrence matrix (GLCM). In study conducted by Medeiros et al [14], the power of these features to deal with the stochastic pattern of corrosion for damage detection in metallic surfaces has been explored. Parameters extracted from the GLCM were used to define similarity properties for corrosion detection purpose in image segmentation methods based on region approach. This approach consists in determining the regions that contain neighbor pixels in the image that have similar properties, that is, gray level and spatial relationship. Two GLCM parameters, namely contrast and energy, are considered to be the most efficient for discriminating different textural patterns.

A wide variety of literature works had reported that texture features are proper to characterize corroded surfaces. In addition, typical color changes of metallic surfaces are often related to corrosion. Thus, color attributes carry out relevant information to design corrosion detection systems and help in building better.

Comparison Table:

S.no.	Previous Research	Algorithm Used	Machine Learning	Features Used
1.	Sindhu Ghanta, Tanja Karp,Sangwook lee	Least Mean Square(LMS)	Supervised Learning	Feature Extraction, Wavelet domain using threshold
2.	Michiko Yamana, Hiroshi Murata, Takashi Onoda, Tohru Ohashi ,Seiji Kato	Support Vector Machine(SVM)	Supervised Learning	Image Data Compression, Correlation Based
3.	Mariana P. Bento, Fatima N. S. de Medeiros, I´alis C. de Paula Jr,Geraldo L. B. Ramalho	Self Organising Mapping(SOM)	Supervised Learning	Feature Extraction, GLCM Based
4.	B.B Zaidan, A.A Zaidan, amdan.O.Alanazi, Rami Alnaqeib	Non-Parametric Classifier	Semi Supervised Mechanism, Machine Learning used	Texture Analysis, Segmentation Based
5.	M.Z. Silva, R. Gouyon[b] ,F. Lepoutre	Lamb waves, Corrosion detection	Artificial Visual Inspection	Laser ultrasonic's , Wavelet analysis
6.	K.Y. Choi ,S.S. Kim	Co-occurrence matrix	Multidimensional scaling procedure	Texture Analysis, Texture Feature
7.	Ramana M. Pidaparti , Babak Seyed Aghazadeh ,Angela Whitfield, A.S. Rao ,Gerald P. Mercier	Image Analysis Algorithm, SEM	Machine Learning is not used	wavelet transforms, Nickel, Modeling Studies, Pitting Corrosion, Acid Corrosion; . Corrosion Fatigue

III. Methodology

After conducting a systematic review and after studying all other possible resources we propose a methodology that covers up the limitation of previous work done and it can be summarized into the following steps:

1. Image Capturing
2. Read Image
3. Convolution of images
4. Run De-noising filter
5. Run Contrast enhancement and Contrast stretching
6. Image Sharpening
7. Run K-means Machine Algorithm
8. Calculate Rust statistics
9. Calculate Rate of Rust Spread

- Image Acquisition & Capturing

Images of the object under study were captured by digital camera SX20IS with specification 12.1 megapixel , 2.8-inch type charge coupled device(CCD) having optical and digital zoom 4x and low light sensitivity .These captured images will then be processed for the detection of the rust.

- Read Image

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After capturing the RGB images which is of size 256*256. The images are then read by function as a matrix and after reading the images some pre processing steps like image cropping and image rotate (if necessary) are done.

- Convolution
  After reading an image, now we convolve the two images to obtain a resulting image of same dimension. Convolution of images is important in this paper because we want to convert it into frequency domain to make calculations easy and to get idea of frequency response. [7].

- Mathematically we can write the convolution as: (i)

$$O(i,j) = \sum_{k=1}^{m} \sum_{l=1}^{n} I(i+k-1, j+l-1)K(k,l)$$

  where i runs from 1 to $M - m + 1$ and j runs from 1 to $N - n + 1$.

- De-noising filter

Now after convolving, De-noising [12] aims at suppressing as much as possible of noise that perturbs a signal or an image. This noise accounts for measurement imperfections (captors of bad quality, quantification noise, etc) and is often model as a Gaussian white noise. Mathematically we can calculate the Gaussian Noise as:

$$h(t) = \frac{\exp\left(\frac{-t^2}{2\delta^2}\right)}{\sqrt{2\pi} \cdot \delta}$$

where

$$\delta = \frac{\sqrt{\ln(2)}}{2\pi BT} \qquad \text{(ii)}$$

where B is the filter's 3-dB bandwidth

- Contrast Enhancement and Contrast stretching

After removing the noise, we improve the perceptibility of objects in the image by enhancing the brightness i.e., the difference between objects and their backgrounds. Contrast enhancements are typically performed as a contrast stretch followed by a tonal enhancement, although these could both be performed in one step [8] and after enhancing we improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the `enhancement' is less harsh [10]. For enhancing the brightness we use a gamma factor that lies in between 0and1. so,if gamma value<1= the image is darkened

if gamma value> 1= the image is brightened overall (iv)

- Image Sharpening

  To get the crisp boundary and crisp edges, we do image sharpening which is one of the most impressive transformations. This will be applying to an image to bring out image detail that was not there before [9]. Paradoxically, the first step in sharpening an image is to blur it slightly. Next, the original image and the blurred version are compared one pixel at a time. If a pixel is brighter than the blurred version it is lightened further; if a pixel is darker than the blurred version, it is darkened. The result is to increase the contrast between each pixel and its neighbours.

- K-means Algorithm

K-means (MacQueen, 1967)[11] is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a 4 clusters. The aim of this algorithm is to grouping the pixels of clusters. In this algorithm we are using RGB images and predominately our images having gray and black colour more than the red and orange colour .More less we try to make 4 types of clusters. Therefore, gray or black part comes under one cluster and light red or dark red in another, then we were able to cluster these group of image pixels into four kinds of clusters representing rust , non-rust and other parts which do not qualify as proper rust and non-rust part and eliminate the remaining ones by using k means and create a logical image which having particular pixels represent rust. Therefore in order to calculate the rate of spread we subtract the whole area from that.

- Calculate Rust statistics

Calculating *Total Rust Area*

Now, the total rusted area of the surface will be calculated. The step will be performed to make sure that the images are partially rusted or totally rusted. Depending on the area

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found rusted important decisions are to be made, whether to repair or discard.

Therefore area can be calculated as:

Non rust area = total count of pixels – total count of rust pixels

Rust area = total count of pixels – total count of non-rust pixels (v)

- Calculating the Rate of Decay

  Rate of decay of the metal will be calculated using time series analysis. Images captured at different times will be compared for reduction in thickness and then rate of decay will be calculated using the standardized formula: mm/y=87.6*(W/DAT) (vi)

  where,

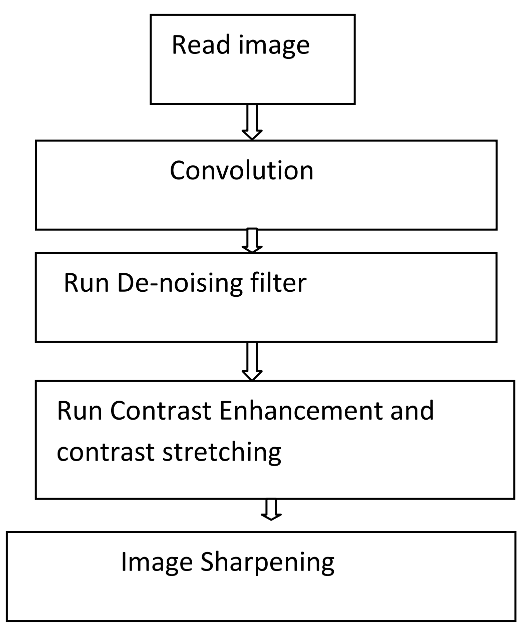
  W= weight loss in mgs

  D = metal density in gm/cm^3

  A= area of sample in cm^2

  T= time of exposure of the metal sample in hours

mm = millimetre per year



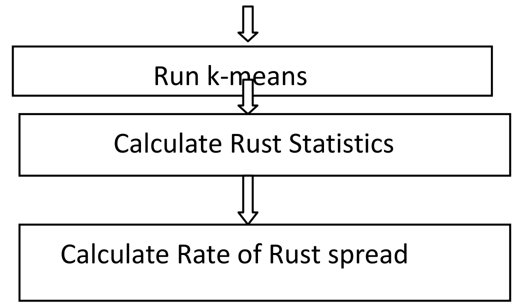


Fig2: Block schematic of rust detection

IV.Conclusion

This paper helps us to detect the rust area from a metal (iron).in this paper we are using unsupervised machine algorithm, with the advantage of having large number of variables, it is computationally faster (if K is small) and also it may produce tighter clusters, especially if the clusters are globular. In this research work, images are captured right from the acquisition stage undergoes certain steps where rate of gradient of the pixels having rust is manipulated in such a way that it leads to reconstruction of new image from which a logical image is built to calculate the rust and non rust part.

V. Future Scope

For future scope, we suggests to develop a representative data set of images depicting rusting of iron at various stages and make a mathematical model depicting rust growth and metal decay using unsupervised machine learning and thresholding to evaluate the validity and performance using time series analysis.

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